Personalized Destination Forecasting and Recommendation: A Multi-Phase AI-Driven Approach for the Tourism Industry

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Abstract. Destination Forecasting and Recommendation encompasses the projection of user-favored travel locales predicated on historical data, individual preferences, and prevailing trends, succeeded by the provision of customized recommendations aimed at optimizing travel arrangements. While current methodologies are hindered by issues related to scalability, computational inefficiency, and a paucity of personalization, they concurrently exhibit deficiencies in reducing inaccuracies such as false positives and false negatives, thereby compromising the reliability of recommendations. To address these challenges, this research introduces a multi-phase AI-driven framework for personalized destination forecasting and recommendation specifically within the tourism sector. The proposed framework initiates with sophisticated data preprocessing methodologies, which include tokenization, stemming, stopword elimination, and TF-IDF, to enhance the quality of the data. Feature extraction is executed via Part-of-Speech (POS) tagging, while the predictive modeling phase amalgamates the computational efficiency of SqueezeNet with the superior feature extraction capabilities of VGGNet through the innovative hybrid architecture known as VGGFire Net. Recommendations are formulated utilizing collaborative filtering techniques alongside Jaccard similarity to accurately discern user preferences. The proposed model achieved outstanding results on Dataset, with 70% training and 30% testing split, the model got 98.55% accuracy, 96.88% precision, 97.78% sensitivity, and 98.44% specificity. For Dataset, with an 80% training and 20% testing split, the model also demonstrated low FPR: 0.0821, FNR: 0.0810. Implemented in Python, this methodology proved its reliability, scalability, and potential to revolutionize personalized travel experiences in the dynamic tourism industry.

Keywords: Destination Forecasting, Recommendation system, Tourism, VGGNet, and SqueezeNet.

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1 Introduction

The way that travel locations are predicted and suggested to travellers has changed as a result of the rapid growth of AI technology in the travel industry and the growing desire for customisation. Londhe et al. [1] traditional mass-market tourism products should give way to more bespoke, soulful experiences that appeal to individual preferences. This has enabled advanced tools of AI, such as ML and DL, which analyse huge amounts of data in predicting effective tourist behavior and preferences. These systems are instrumental in tailoring travel itineraries, optimizing resources, and enhancing the tourism experience. Zhou, et al.[2] economic forecasting is the backbone of strategic decision-making in tourism; AI technologies significantly improved the accuracy and reliability of such forecasts. AI-driven predictive models help stakeholders in the tourism industry to predict market trends, make informed decisions, and fulfill the changing needs of consumers. Zhang et al. [3] further elaborate on AI's role in mitigating global challenges, elaborating on its potential for integrating with environmental and economic policies, such as green finance and energy transitions, into the promotion of sustainable tourism development.

Social media (SM) and user-generated content (UGC) also transform the decision-making process for traveling. Florido-Benítez et al. [4] SM and UGC are significant touchpoints for travelers, with much information available that influences the expectations and destination choices of travelers. AI-based sentiment analysis and recommendation systems utilize this content to enhance marketing strategies in a targeted and engaging approach. Florido-Benítez et al.[5] discuss the integration of AI in tourism marketing data-driven algorithms to customize promotional activities to the specific requirements of individual consumers. That in itself enhances customer interaction while ensuring a better return on investment for the tourism business. Similarly, trace the historic evolution of distribution channels within tourism, from traditional agencies to AI-enabled platforms that provide real-time inventory management along with seamless booking experiences

The concept of Smart Tourism Destinations (STDs) symbolizes the intersection of AI and digital innovation. Suanpang et al.[6] AI, augmented reality (AR), and other emerging technologies enhance the accessibility and governance of STDs. These technologies allow hyper-connected tourists to navigate destinations more efficiently, enrich cultural experiences, and access immersive virtual environments. Woo-Je et al.[7] describes the computerized reservation systems and GDS, which transformed the travel booking process, establishing the foundation for the AI-driven platforms of today. From this base, connect these technological innovations to wider economic indicators as AI supports sustainable tourism, countering issues such as urbanization and climate change.

Gurung, et al. [8] also highlight the necessity of pattern recognition systems, which are used to analyze complex consumer behavior and detect market trends. These systems, powered by AI, are integral to creating personalized travel experiences and implementing dynamic pricing strategies. As a result, it allows tourism businesses to operate efficiently and, at the same time, improve customer satisfaction. As noted by Renjithet al. [9] with economic significance in the tourism sector accounting for 10.2% of global GDP, the need to stay innovative is necessary for continuing growth. AI technologies give a very effective approach by streamlining processes, adding effect to marketing, and introducing value-driven services to serve tourists.

Major contribution of this paper is to introduce VGGFire Net, a hybrid model combining VGGNet and SqueezeNet, to enhance prediction accuracy and computational efficiency. SqueezeNet increases performance by lowering the number of variables with its small firing modules, whereas VGGNet is selected for its deep feature extraction abilities, which make it perfect for identifying intricate patterns. Together, they balance high performance and low resource consumption, making VGGFire Net effective for personalized recommendation systems.

The work is organized as follows: A review of the pertinent literature is presented in Section 2. The suggested approach is explored in Section 3, and the findings are discussed in Section 4. The work is concluded in Section 5.

2 Literature review

Mishra *et al.*[10] discussed the global influence of Artificial Intelligence (AI) in all sectors, including tourism. AI's fast processing rate is transforming sectors like health, finance, and manufacturing, and it is substantially changing the tourism sector. The visitor experience, operational efficiency, and sustainability in tourism have been enhanced by AI.

Zhang *et al.*[11] improved the precision of modeling and developed AI-based techniques for predicting tourism demand. Two fundamental issues lead to overfitting in DL models that forecast demand for tourism: (1) availability to large amounts of data and (2) the need for additional explanatory variables.

Badouch & Boutaounte [12] discussed the use of ML algorithms in recommender systems for personalized tourism experiences. According to the explanation, such platforms employ user data to make suggestions for locations, tasks, lodging, and destinations according to user preferences and activity.

Kanimozhi *et al*. [13] talked about a customized travel and tourism route suggestion system that makes application of geotagged images and user-generated data from social media to suggest destinations. The suggested system provides an enhanced user profile using the User-Location Vector, applying Latent Dirichlet Allocation (LDA) with Jaccard Coefficients in generating the recommendation.

Nabila [14] discussed the changing dynamics of the tourism sector through the Fourth Industrial Revolution. It covers the use of AI, digital change, and new technologies that lead to the establishment of smart cities and the production of excellent tourist attractions.

Suanpang & Pothipassa[15] introduced a new way to make smart tourism destinations more inclusive, based on the integration of Gen AI, NLP, and the IoT, as a component of an avenue for organizing trips and tourist choices. Agile methodology was applied to the development, where information provision, predictive analytics, personalized recommendation, and multilingual communication are presented across three tiers.

Pai *et al*. [16] discussed the growing role of smart tourism technology in attracting tourists and enriching their experience for travel. It centered on smart technology and visitor happiness, incorporating safety, customization, availability, interactive features, and informational value.

Ma[17] introduced a tourism industry, which is crucial to world economic growth, though such an industry face overcrowding and cultural barriers. AI can bring promising solutions through personalized experience, improvement in operations, and enhancing safety. Innovations like machine learning, virtual assistants, augmented reality, and virtual reality will provide specific suggestions and deep immersion.

Şeker [18] discussed the potential use of AI along with mathematical modeling to predict Turkey's tourism receipts. Among the most popular travel destinations worldwide is Turkey, but still, its tourism revenue does not feature in the top ten globally. The study shows that among the types of expenditures made, accommodation and food & beverage are major sources of revenue for the tourism industry in Turkey and predicts that the total will not go beyond 45 billion dollars by 2027.

Mohammad Shafiee [19] explored the use of AI and smart tourism technologies to counter over-tourism in tourist destinations. Overtourism results in environmental degradation, strain on resources, and decreased visitor satisfaction, threatening the sustainability of these destinations. The study reveals that the advanced technologies of IoT, AR, VR, and big data analytics can optimize resource usage, enhance visitor engagement, and promote responsible tourism practices.

2.1 Problem Statement

The tourism industry is transforming with AI and smart technologies enabling personalized recommendations, efficient resource allocation, and sustainability. However, challenges like overfitting in predictive models, insufficient explanatory variables, and limited data hinder the accuracy and scalability of AI-driven systems. Issues such as over-tourism lead to environmental degradation, resource stress, and reduced visitor satisfaction, emphasizing the need for responsible management strategies. Technologies like IoT, AR, and VR offer solutions to optimize resource use and manage tourist flows but require better planning, investment, and collaboration. Advanced analytical models are essential for understanding expenditure patterns and data-driven decision-making, necessitating an integrated, multi-phase approach for seamless, inclusive, and sustainable tourism experiences addressing operational and environmental challenges.

3 Proposed Methodology

The study suggests a multi-phase procedure for precise, personalized destination forecasting and recommendations in the dynamic hospitality and tourism industry. It begins with advanced data preprocessing using tokenization, stemming, and stopword removal and TF-TDF to enhance data quality.

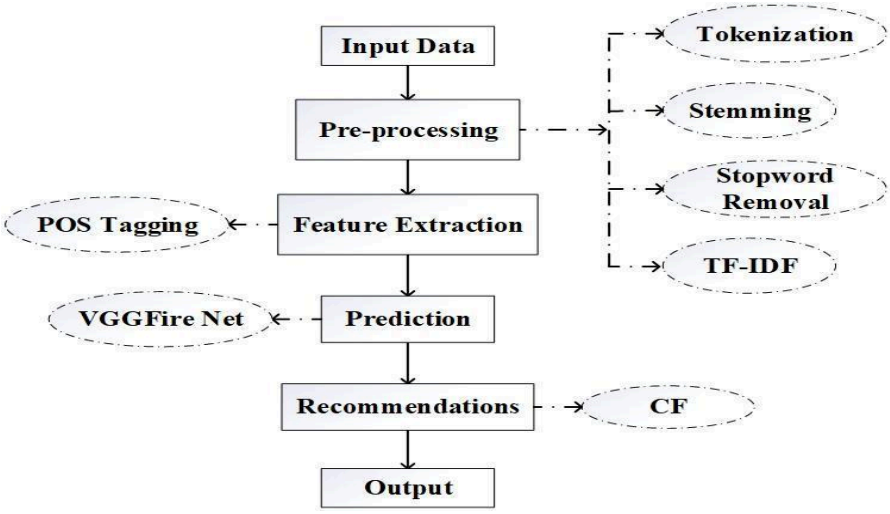

Fig 1. Overall Architecture of the proposed model

Critical feature extraction employs BERT, followed by predictive modeling using SqueezeNet for computational efficiency and VGGNet for high performance.

Personalized recommendations are delivered through collaborative filtering techniques. The overall design of the suggested framework is depicted in figure 1.

3.1 Data collection

The dataset employed in the study is the Tripadvisor multi criteria (MC) dataset. The TripAdvisor MC dataset consists of user-rated hotel MC ratings, with a value between 1 and 5. The TripAdvisor dataset also includes 28,829 multi-criteria ratings on seven other criteria: general level of service, registration value for cash, room hygiene, room setting, and corporate level of service.

3.2 Pre-processing

Pre-processing is the procedure of cleaning and converting unformatted text into a machine-readable format. Tokenization, stemming, stopword removal, and IF-TDF are utilized to pre-process the data in this study.

Tokenization The procedure of tokenizing sentences involves dividing them into words, characters, and punctuation, which are all known as tokens. The primary separating criterion occurs when a punctuation mark or space appears. This stage aids in eliminating undesirable words for subsequent processing stages.

Stop Words Removal Except for a few specific usage scenarios, words like "the," "are," "is," "and," and so on have no significance in NLP. For example, in the application scenario for text or content categorization, additional phrases are not given any weight. Only the search terms that comprise the concepts are collected. Thus, the more these StopWords are identified and cleared up, the better the results of categorization systems. It's also critical to keep in mind that in certain use scenarios, like interpersonal designs, the application of particular negation words, such as "No," "cannot," "won't," and "not," is essential to comprehending the setting and significance of the phrase.

Stemming Stemming is an aggressive word-shortening technique that aims to simplify a term to its simplest form. The suffixes are eliminated to bring it down to the simple root, yet each form retains its meaning significance. However, this isn't usually effective since the phrase loses its literal meaning.

TF-IDF The importance of a word to a document within a set is shown by a statistical measure known as TF-IDF. The TF-IDF is a frequently used weighting parameter for data extraction and text mining. The score of TF-IDF increases in a direct correlation to the number of occurrences a word appears in the file, despite being offset by the

term's frequency in the data set. This is one technique to deal with the reality that certain phrases are frequently more common than others. TF-IDF is a useful tool for stop-word filtering in a number of fields, including text summarization and classification. TF-IDF is calculated by multiplying two data: frequency and inverse document frequency. To better differentiate every word, the number of instances it shows up in each document is counted and combined altogether. A term's TF is the number of times it occurs in an article.

$$TF_{(t,d)} = 0.5 + \frac{0.5*F_{(t,d)}}{Maximum\ occurance\ of\ words} \tag{1}$$

IDF: To determine a word's relevance inside a group of written documents, an empirical weight known as an IDF is employed. By adding the IDF characteristic, the weight of words that occur regularly in the file collection is decreased and the weight of words that occur rarely is increased.

$$IDF_{(t,d)} log = \frac{|D|}{(no\ of\ doc, term\ t\ appearns)} \tag{2}$$

Next, each word's Term Frequency - Inverse Document Frequency [TF-IDF] is determined utilizing the formula,

$$TF - IDF_{(t,f,d)} = TF_{(t,d)} * IDF_{(t,d)} \tag{3}$$

In equations (1) and (2) $t, f\ and\ d$ represents the frequency with which the term t appears in document d. Equation (3) uses Term Frequency ($TFt,\ d$) and Inverse Document Frequency ($IDFt,\ d$) to calculate TF-IDF for each term in the document.

3.3 Feature Extraction

Finding and removing pertinent features from unprocessed text data is known as feature extraction. In this study, the pre-processed data is input into the feature extraction phase, where POS Tagging is employed to extract relevant features.

POS Tagging The process of assigning a noun, pronoun, verb, adjective, preposition, and other basic grammatical classes to the words in a phrase is known as POS tagging. Similar to how a human assigns parts of speech, the POS tagger takes the sentence's context into account. Additionally, the POS tagger can recognize the elements of speech more easily if the sentence segmentation is done well. Using the wrong sentence boundary would result in horrible mistakes.

3.4 Prediction using VGGFire Net

The extracted features are subsequently passed to the prediction model, known as VGGFire Net, which is a hybrid architecture combining the strengths of SqueezeNet and VGGNet.

SqueezeNet A SqueezeNet's fundamental concept is to use as few parameters as possible while maintaining an appropriate level of accuracy. Three concepts were proposed in the design of this architecture. First, 1x1 filters were used, which contain less parameters than 3x3 filters. Squeeze layers were used to minimize the number of input channels to 3x3 filters, which always results in less network weights at the second stage. At the third stage, the network is downsampled to produce large activation maps. A convolution layer with the same number of data classes and output channels takes the place of the fully connected layers. The dropout layer and softmax activation function come next. The building component that aids in the effective deployment of the three stages is the fire module. The squeeze net's most instructive elements were taken out.

VGGNet A DCNN known for its ease of use and outstanding picture identification capabilities is VGGNet. variations like VGG16 and VGG19, which have 16 and 19 convolutional layers, accordingly, are distinguished by their deep structure. ReLU activations, max-pooling layers for spatial downsampling, fully connected layers for classification, and a sequence of 3x3 convolutional layers are all used in these algorithms. The "deep" nature of VGGNet refers to its numerous layers, which enable the extraction of hierarchical features for precise object identification. Originally developed for the ImageNet dataset, VGGNet has proven to be versatile, outperforming benchmarks across various tasks and datasets. Its consistent architecture, combined with its effectiveness in feature extraction, makes it a foundational model for innovative object detection and recognition applications.

VGGFire Net- The study introduces a hybrid model, VGGFire Net, which combines the strengths of SqueezeNet and VGGNet to enhance prediction accuracy and computational efficiency for personalized recommendation systems. figure 2 shows the overall architecture of the VGGFire Net model.

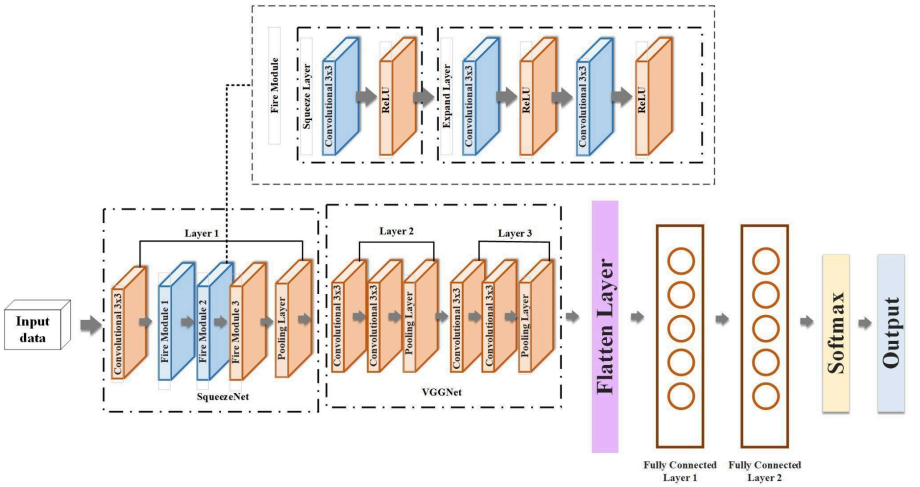

Fig. 2. VGGFire Net model

In this model, VGGNet plays the role of deep hierarchical feature extraction, using its multiple convolutional layers to capture complex patterns and build high-level abstractions from data, making it ideal for tasks that require recognizing intricate features. On the other hand, SqueezeNet contributes to computational efficiency by incorporating its compact and efficient fire modules into the initial layers of VGGNet. A squeeze convolution layer with 1x1 filters and an expand layer with a combination of 1x1 and 3x3 convolution filters make up these fire modules. By decreasing the number of variables, especially in the early layers, the fire module's primary adjustable hyperparameters—s1×1, e1×1, and e3×3—optimize the network. The fire module restricts the input channels to the 3×3 filters by making sure that s1×1 is less than the sum of e1×1 and e3×3, which lowers storage and computational needs without compromising speed. This integration allows VGGFire Net to achieve fast feature extraction while maintaining VGGNet's deep learning capabilities in the later layers, ensuring a balance between computational efficiency and depth. As a result, VGGFire Net can handle large datasets effectively, making it ideal for real-time applications such as personalized destination recommendations in the tourism industry. Moreover, this hybrid approach enhances scalability, adaptability, and precision, making it suitable for a wide range of recommendation-based systems in tourism.

3.5 Recommendations via CF

The predicted outcome is then passed to the recommendation model, which generates recommendations based on the user's preferences. In this section, the recommendations provided through CF.

CF The predicted outcome produced by the VGGFire Net is passed to the recommendation model, which generates recommendations based on user preferences. Here, collaborative filtering (CF) is used to pinpoint the key elements in the design of a RS. Investigations show that the suggested approach enhances the tourism destination RS's stability and efficacy. Travel planning gets simpler than ever before with the use of a RS built on CF and data mining. The data is interpreted to take into account consumer tastes and changing circumstances before being suggested to users. For each of the suggested tourist attractions close to their current place, users will require comprehensive details and directions. The tourism suggestion program is run and controlled by local tourism agencies, smartphone apps, and webpages.

Calculate Weight: Compute the weight for all users based on semantic similarity.

Similarity Calculation: The Jaccard Similarity method is used to find similarity between rating vectors. The method is described as:

$$Jaccard\ Similarity\ (A,\ A^{'}) = \frac{\left|V_A \cap V_{A^{'}}\right|}{\left|V_A \cup V_{A^{'}}\right|} \tag{4}$$

V_A The set of destinations rated by user A. $V_{A^{'}}$ is the set of destinations rated by user $A^{'}$. $V_A \cap V_{A^{'}}$ is the set of destinations that both users have rated (the intersection of their rated destinations). $V_A \cup V_{A^{'}}$ is the set of all unique destinations rated by either user (the union of their rated destinations). The Jaccard Similarity value ranges from 0 to 1, where 0 indicates no similarity (no destinations in common) and 1 signifies identical ratings for all destinations, with a higher value indicating greater similarity between users based on the items they have rated.

Selecting Neighbors: After calculating the similarity, pick the users with the highest similarity to the active user.

Prediction Calculation: Calculate the prediction from a weighted aggregation of the selected neighbors' ratings using the following weighted formula:
p(a,i)=ru+∑i=1n|Jaccard Similarity(u,uj)|∑i=1n(ruj−ru)·Jaccard Similarity(u,uj)

$$q(A,i) = ave_A + \frac{\sum_{i=1}^{n}\left(ave_A - ave_{A^{'}}\right) \cdot Jaccard\ Similarity(A, A^{'})}{\sum_{i=1}^{n}\left|Jaccard\ Similarity(A, A^{'})\right|} \tag{5}$$

Where $q(A,i)$ is the predicted rating for destination i by user A, ave_A is the average rating of user A, $ave_{A'}$ is the rating of user A' for destination i.

Recommendation: This performance enhancement is achieved through the use of Jaccard Similarity as the primary measure for user similarity. Jaccard Similarity effectively captures the shared preferences between users by comparing the set of items they have rated, making it computationally efficient and well-suited for the dynamic and personalized nature of tourism recommendations. By focusing on the similarity between users, the system is able to recommend tourism destinations based on users' unique preferences and contexts, thus improving the precision and personalization of recommendations. By enabling customized travel preparation, this method not only improves the user experience but also increases the precision of location recommendations.

4 Result and Discussion

The efficacy of the suggested framework is compared with that of the current methods, such as RNN, CNN, ANN, and PSO-LSSVM, in the next section. The suggested framework is executed on the Python platform. Metrics such as accuracy, precision, sensitivity, specificity, FNR, MCC, FPR, and NPV are used to assess efficiency.

4.1 Performance metrics

Accuracy: The ratio of samples that were successfully identified to all samples is used to determine accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

Precision: Out of all the samples that were predicted to be favorable, accuracy quantifies the proportion of samples that were correctly identified as affirmative.

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

Sensitivity: The proportion of true positive samples that were correctly classified as positive is measured by sensitivity.

$$Sensitivity = \frac{TP}{TP+TN} \tag{8}$$

Specificity: Specificity is determined by how many actual negative samples are correctly categorised as negative.

$$Specificity = \frac{TN}{TN+FP} \tag{9}$$

F-Measure: It is the harmonic mean of recall and precision

$$F - Measure = \frac{2*precision*recall}{Precision+recall} \tag{10}$$

FPR: The FPR calculates the proportion of really negative samples that were mistakenly classified as positive.

$$FPR = \frac{FP}{FP+TN} \tag{11}$$

FNR: FNR calculates the proportion of true positive tests that were incorrectly classified as negative.

$$FNR = \frac{FN}{TP+FN} \tag{12}$$

MCC: MCC spans from -1 to +1 and integrates data regarding true and false positives and negatives into a single value, where +1 denotes a perfect classification, 0 denotes random categorization, and -1 denotes the full discrepancy between prediction and observation.

$$MCC = \frac{((TP*TN)-(FP*FN))}{\sqrt{((TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)}} \tag{13}$$

NPV: NPV calculates the percentage of real negative samples that were correctly identified as being negative out of all samples that were expected to be negative.

$$NPV = \frac{TN}{TN+FN} \tag{14}$$

where FP is the number of wrongly unfavourably categorized instances, FN is the number of wrongly categorized constructively categorized instances, TP is the number of properly categorized strongly categorized instances, and TN is the number of properly categorized adversely categorized instances.

4. 2 Performance Evaluation

Table 1: Comparison of existing model and proposed model (70% training and 30% testing)

	PSO-LSSVM	RNN	ANN	CNN	VGGFireNet
Accuracy	79.56743	91.77654	88.98765	95.55443	99.12345
Precision	73.45534	86.55678	81.77654	90.44321	97.44321
Sensitivity	74.65422	87.43321	84.55443	89.98765	96.87654
Specificity	81.23455	90.12345	87.66544	91.55443	98.55443
F-Measure	76.55678	89.4321	83.77654	92.44321	96.77654
MCC	77.12345	87.55543	85.12345	93.55443	98.55443
NPV	78.65433	89.77654	86.87654	89.77654	97.98765
FPR	0.311098	0.244333	0.240987	0.207654	0.089123
FNR	0.299876	0.260987	0.225443	0.185443	0.073321

Table 2. Comparison of existing model and proposed model (80% Training and 20% Testing)

	PSO-LSSVM	RNN	ANN	CNN	VGGFireNet
Accuracy	80.6655	92.8876	89.8765	94.3321	98.55443

Precision	74.3321	88.4432	83.1234	91.5544	96.87654
Sensitivity	73.1234	87.6655	84.9876	90.8765	97.77654
Specificity	82.8765	91.5544	88.7654	92.7765	98.44321
F-Measure	77.54321	90.87654	86.55443	89.55443	95.98765
MCC	75.8765	89.7654	87.6655	90.4432	96.87654
NPV	79.8765	88.6655	88.9876	86.5544	99.12345
FPR	0.30876	0.19587	0.25543	0.17332	0.08211
FNR	0.29544	0.19865	0.23087	0.18543	0.080987

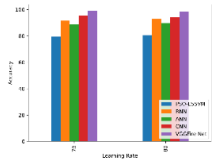

Figure 3 (a): Accuracy

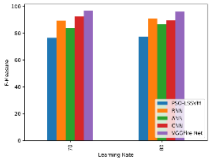

Figure 3 (b): F-Measure

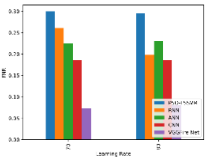

Figure 3 (c): FNR

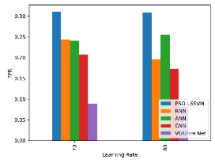

Figure 3 (d): FPR

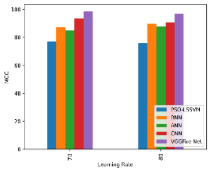

Figure 3 (e): MCC

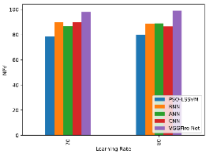

Figure 3 (f): NPV

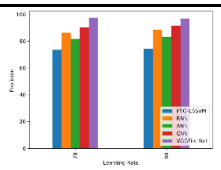

Figure 3 (g): Precision

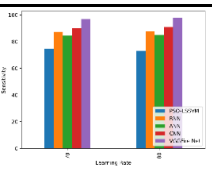

Figure 3 (h): Sensitivity

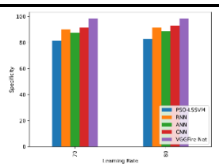

Figure 3 (i): Specificity

Fig. 3 Comparative performance analysis of models including PSO-LSSVM, ANN, CNN, VGGNet

Figure 3 (a) – 3 (i) presents a comparative performance analysis of models including PSO-LSSVM, ANN, CNN, VGGNet, and the proposed VGGFire Net, evaluated with 70% training and 30% testing (Table 1), and 80% training and 20% testing (Table 2). The metrics assessed are Accuracy, F-Measure, Precision, Sensitivity, Specificity, FNR, FPR, MCC, and NPV. VGGFire Net consistently outperforms other models, achieving the highest accuracy, precision, sensitivity, and specificity. It also demonstrates minimal FNR and FPR, highlighting its superior reliability, scalability, and precision for personalized destination forecasting and recommendation.

4.3 Discussion

Figure 4 displays a hotel recommendation interface where users can input their location to find the best hotel options, such as Park Hyatt Sydney and Shangri-La Hotel Sydney. The system provides detailed reviews and ratings for these hotels, highlighting excellent ratings (all set at 5.0) in service, cleanliness, overall value, location, sleep quality, and rooms, along with similar hotels like Hotel ZaZa Houston and Montage Laguna Beach for comparison.

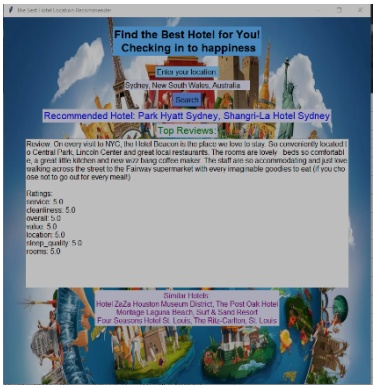

Fig. 4. Personalized Hotel Location and Recommendation System

Relating this to the proposed VGGFire Net model, the model's exceptional performance is evident with an accuracy of 98.55%, precision of 96.88%, sensitivity of 97.78%, and specificity of 98.44%. This high accuracy value indicates the model's ability to reliably predict and recommend high-quality hotels, minimizing recommendation errors with low false positive (0.0821) and false negative (0.0810) rates. The model's outstanding accuracy ensures precise, trustworthy hotel recommendations, akin to a dependable and effective hotel recommendation system.

5 Conclusion

This study developed a multi-phase AI-driven methodology to address the limitations of existing destination forecasting and recommendation approaches, such as scalability, computational inefficiency, and limited personalization. Advanced preprocessing techniques, including tokenization, stemming, stopword removal, and TF-IDF, were employed to enhance data quality, while POS tagging was used for feature extraction. The hybrid VGGFire Net model, combining the computational efficiency of SqueezeNet with the high performance of VGGNet, formed the core of the predictive framework. Personalized recommendations were generated using collaborative filtering and Jaccard similarity, ensuring accurate identification of user preferences. The proposed model achieved outstanding results on Dataset, with 70% training and 30% testing split, the model obtain 98.55% accuracy, 96.88% precision, 97.78% sensitivity, and 98.44% specificity. For 80% training and 20% testing split, the model also demonstrated low error rates (FPR: 0.0821, FNR: 0.0810). Implemented in Python, this methodology proved its reliability, scalability, and potential to revolutionize personalized travel experiences in the dynamic tourism industry.

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